Assignment 1 Report

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Introduction

This report analyses image processing techniques to distorted images to detect structural lines, rectify perspective distortions, and assess image quality. The main methods employed in this study include geometric transformations for perspective correction, RANSAC for filtering false detections, Hough Transform for straight-line detection, and SSIM (Structural Similarity Index Measure) for picture quality assessment. Both qualitative visual comparisons and quantitative SSIM evaluations are used to assess how well these methods perform in terms of how closely the processed photos resemble the ground truth.

Method

Hough Transform for Line Detection

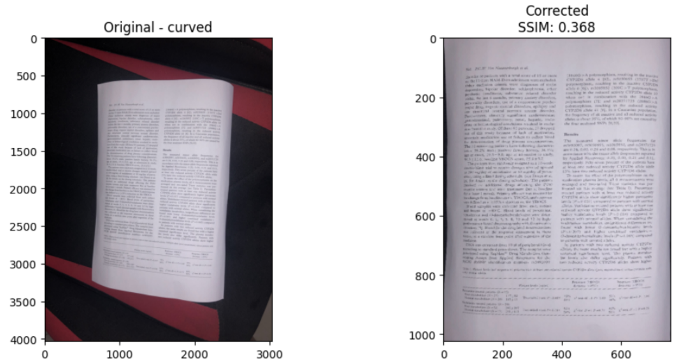
The first stage of the process involves detecting straight lines in the distorted images using the Hough Transform. This method is particularly useful for identifying lines even when they are partially broken due to noise or when there is significant background clutter. Transforming edge points into a parameter space allows for a voting mechanism to determine the most probable lines in an image. The process begins with edge detection, typically performed using the Canny Edge Detector, to highlight significant edges in the image. These edge points are then transformed into a polar coordinate space where each point corresponds to a set of possible lines. A voting system is used to accumulate evidence for line candidates, and the highest-scoring parameters are selected as detected lines. Despite its effectiveness, the Hough Transform has limitations. One of the main issues is the tendency to detect unwanted or false lines, especially when the image contains excessive noise. Since the method relies on edge detection, inaccuracies in edge maps can directly affect the quality of detected lines. Additionally, in images with dense structures, the Hough Transform may detect multiple overlapping lines, requiring additional refinement to extract meaningful results.

RANSAC for Outlier Removal

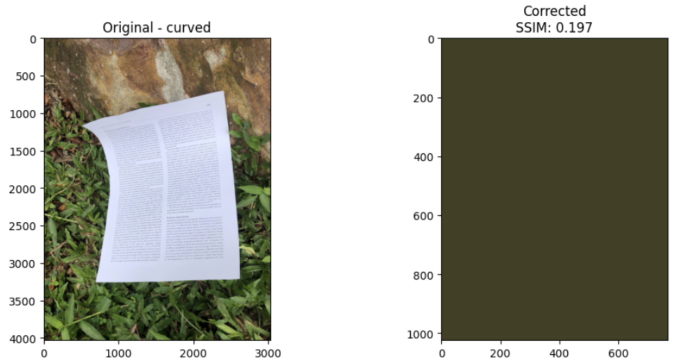
To refine the results obtained from the Hough Transform, RANSAC (Random Sample Consensus) is applied as a filtering step. RANSAC is an iterative algorithm that is highly effective in removing outliers and ensuring that only meaningful structural lines are retained. It works by randomly selecting a subset of detected points and fitting a line model to them. The model is then evaluated based on the number of inliers—points that fit the model within a certain threshold. This process is repeated multiple times to identify the best-fitting model with the maximum number of inliers. One of the key advantages of RANSAC is its robustness against noise and outliers. Unlike least-squares fitting, which is highly sensitive to erroneous data points, RANSAC can discard incorrect detections and retain only reliable structural lines. However, RANSAC also has some limitations. Its performance depends on the ratio of inliers to outliers—if the image contains too much noise, RANSAC may struggle to find a strong model fit. Additionally, it requires a predefined threshold for inlier selection, and improper tuning of this parameter can lead to either excessive filtering or the retention of false positives. By applying RANSAC after the Hough Transform, the overall accuracy of line detection is improved, ensuring that only the most structurally significant lines are used in further processing steps such as perspective correction.

Some Images

Below are examples of the different distortion categories (rotate, curve, fold, random, incomplete, perspective) encountered in this assignment. Each category presents unique challenges that require specific corrections to improve image alignment and quality.

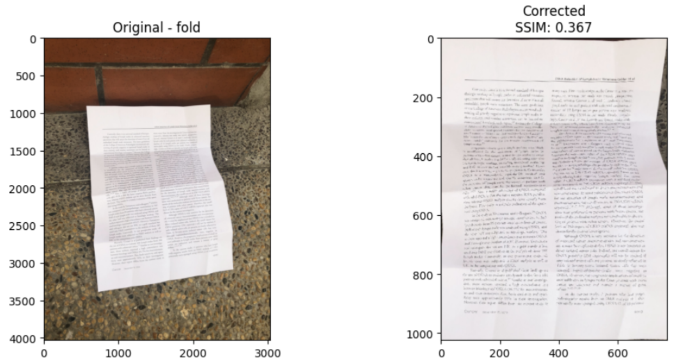


(a) Better Result

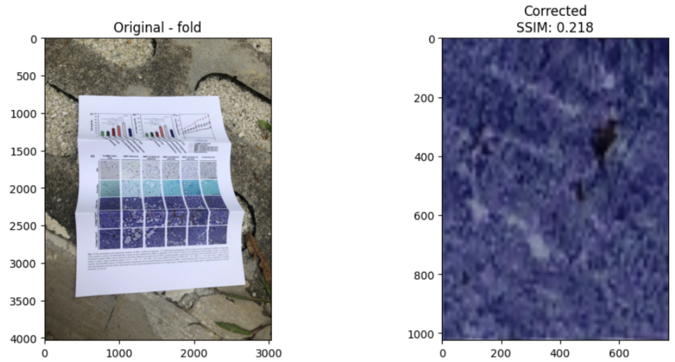


(b) Worse Result

Figure 1: Example for Curved Fixation in the dataset.

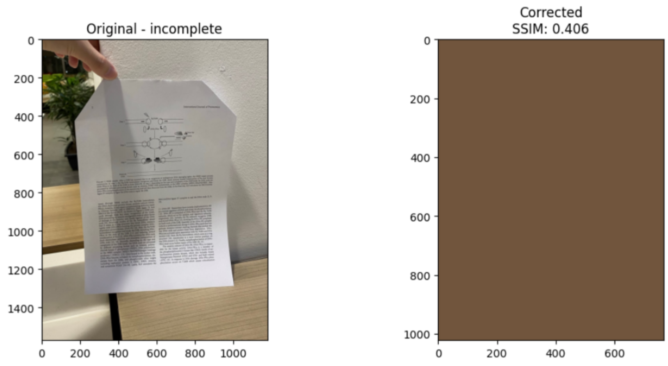


(a) Better Result

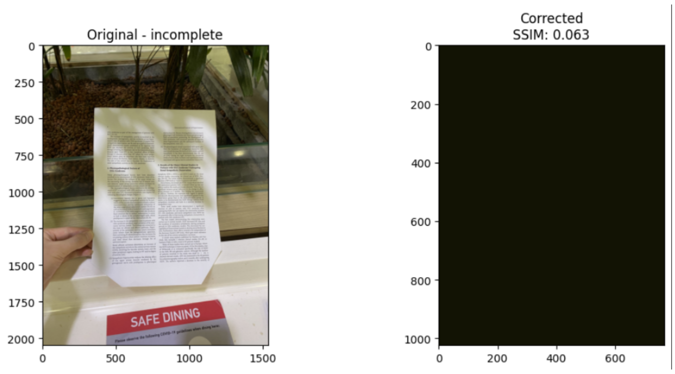


(b) Worse Result

Figure 2: Example for Fold Fixation in the dataset.

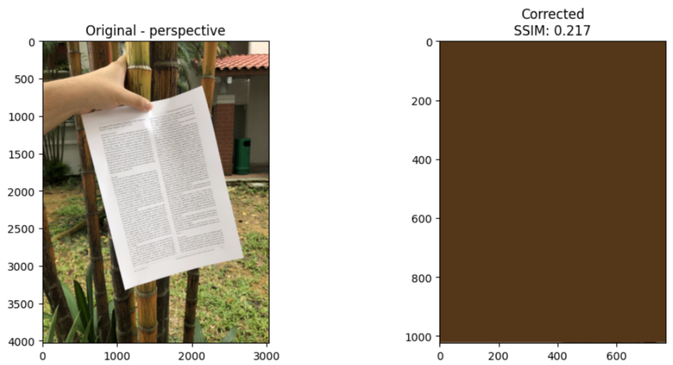


(a) Better Result

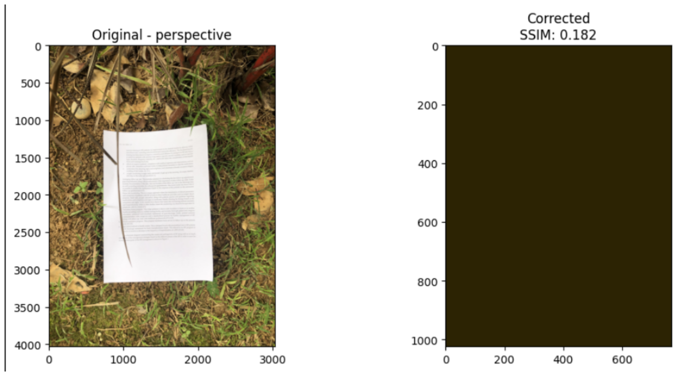


(b) Worse Result

Figure 3: Example for Incomplete Fixation in the dataset.

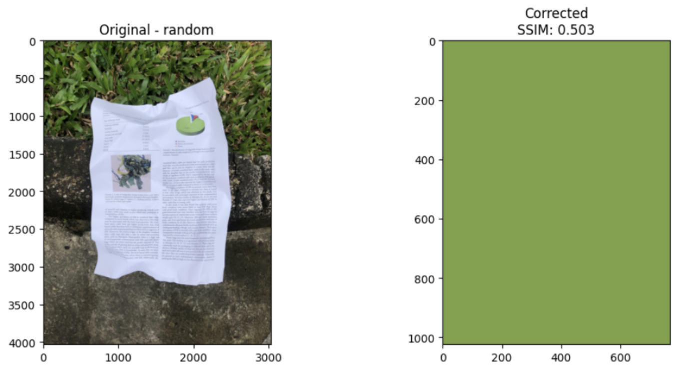


(a) Better Result

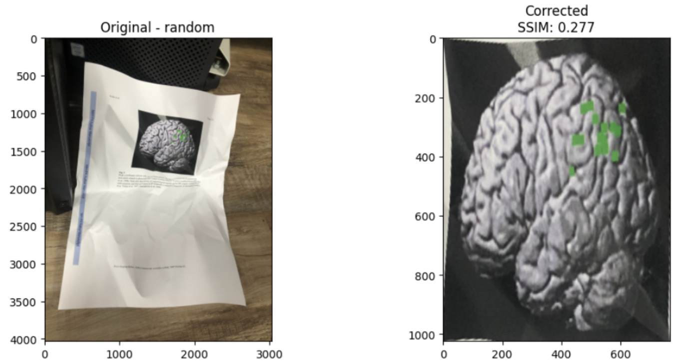


(b) Worse Result

Figure 4: Example for Perspective Fixation in the dataset.

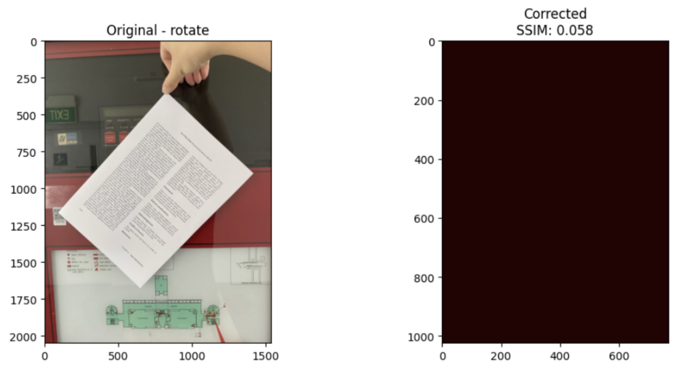


(a) Better Result

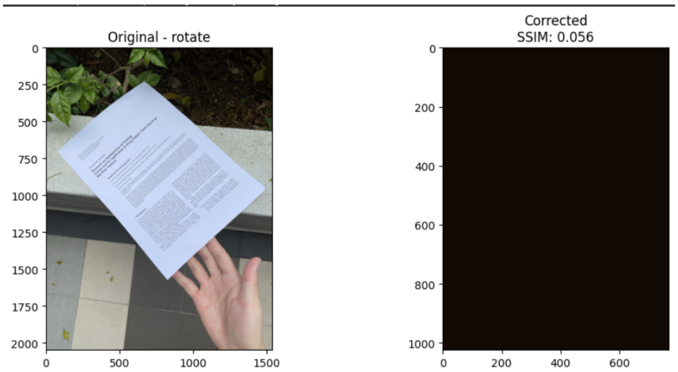


(b) Worse Result

Figure 5: Example for Random Fixation in the dataset.



(a) Better Result



(b) Worse Result

Figure 6: Example for Rotate Fixation in the dataset.

Results

The performance of the applied methods is evaluated through both visual comparisons and SSIM assessments. The original images exhibit noticeable distortions, while the Hough Transform detects structural lines, including both correct and false positives. RANSAC refines these detections by filtering unreliable lines, ensuring that only the most significant features remain. Perspective correction further enhances image alignment, making the final output more comparable to the ground truth.

SSIM scores provide a quantitative measure of these improvements. The rotate category achieves the highest mean SSIM score (0.378978), while the random category has the lowest (0.305520). The curved category shows the highest standard deviation (0.172895), indicating greater variability in similarity scores, whereas rotate has the lowest (0.134851), reflecting more consistent performance. In terms of maximum SSIM values, incomplete images achieve the highest similarity (0.761895), while fold has the lowest (0.602657), suggesting limitations in its correction process.

You can see all results from experiments on Table 1.

	Min SSIM	Max SSIM	Avearage SSIM
Curved	*0.015*	0.751	0.259
Incomplete	*0.063*	0.762	0.314
Fold	*0.004*	0.606	0.272
Random	*0.008*	0.676	0.274
Rotate	*0.031*	0.658	0.343
Perspective	*0.029*	0.756	0.299

Table 1: Results from experiments.

Despite these enhancements, some challenges persist. The Hough Transform tends to detect extra lines, leading to false positives, and RANSAC's effectiveness is influenced by the ratio of inliers to outliers, making it less reliable in highly noisy images. Perspective correction is also sensitive to reference point selection, where minor errors can introduce distortions. Potential improvements include adaptive Canny edge detection to refine edge maps, weighted RANSAC to prioritize reliable inliers, and deep learning-based approaches such as holistically nested edge detection for more robust line detection.

This study demonstrates the effectiveness of Hough Transform, RANSAC, and perspective correction in enhancing distorted images. While these techniques improve structural alignment and reduce artifacts, challenges remain in optimizing their parameters and handling noise. Future research could explore advanced filtering techniques and deep learning-based models to further improve robustness and accuracy in distorted image processing.